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Abstract

In this paper we analyse the interactions between, and determinants of, test scores, truancy and the risk of youth unemployment and NEET in a simultaneous equations framework. This approach allows us to disentangle the observable direct and indirect effects of truancy and test scores on the risk of unemployment and NEET from their unobserved effects. We use a unique data source, combining the Youth Cohort Study, the School Performance Tables, and the School's Census, enabling us to control for a large number of personal, family, school, peer group and neighbourhood effects on the three response variables. Our findings suggest that models of the determinants of youth unemployment and NEET that ignore correlation between

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the unobservables of the determinants test scores and truancy will lead to misleading inference about the magnitude and strength of their direct effects. However, our findings also suggest that truancy has a indirect effect on labour market outcomes via its effect on test scores. Truancy does have an unobserved effect on the risk of unemployment and the risk of NEET insofar as the correlation between latent variables for truancy and labour market outcomes are positive and statistically significant. Test scores have a direct effect on labour market outcomes, and through the estimation of ATTs, we show a good performance in high stakes tests (i.e. GCSEs) can mitigate the effect of truanting from school on labour market outcomes.

JEL Classification: I21, J64.

JEL Classification:

1 Introduction

The youth unemployment rate has been rising since 2004, pre-dating the 2008 recession, following a fairly predictable pattern with regard to cyclical downturns (Petrongola and van Reenen, 2011).[1] Although it is difficult to pin down the causes of the rise in youth unemployment, one possible cause highlighted by Petrongola and van Reenen (2011) is the quality of schooling. Furthermore, what is very clear from their analysis of LFS data is that the unemployment rate for 16-17 year olds was as high in 2010 as it was in the last major recession in 1980 - exceeding 30%. However, official measures of youth unemployment, and teenage unemployment

[1] Youths are often defined as those aged 16-24 years, however, it is often the case that a distinction is made between teenagers (aged 16-19) and the rest because the former have very little work experience or skills.

in particular, are likely to understate the true magnitude of joblessness for this group given the propensity of some youths to drop out of the labour market and remain economically inactive for periods of time. A better measure of the labour market fortunes of youths is therefore likely to be the proportion of the group who are 'Not in Education, Employment or Training' (NEET) - the unemployed and economically inactive. Since this group of young people are not engaged in skill formation of any kind they are most likely to be 'scarred' by this early labour market experience.

Previous research has, in fact, shown that a poor start to a young persons career can lead to an increased probability of unemployment, as well as a negative effect on future earnings. Aralampulam et al (2001) have shown that earnings can be 6% lower on re-entry to a job and 14% lower after 3 years - the most damaging spell of unemployment is the first. Clark, Georgellis and Sanfey (2001) also show that past unemployment is correlated with current life satisfaction, an additional dimension to the scarring effect, although Knabe and Ratzel (2011) have recently shown that this effect operates via a fear of future unemployment. (See also Bell and Blanchflower, 2011, 2012). Mroz et al (2007) provide a counter argument suggesting that, whilst earnings growth can be retarded, young workers who experience spells of unemployment can respond by acquiring human capital which reduces the risk of future spells of unemployment.

This paper focuses on the labour market outcomes of the teenage group (16-17 year olds) and assesses the interdependencies between test scores and truancy behaviour, both of a function of school quality, and the risk of unemployment or NEET several months after leaving school.[2] There has been considerable debate in

[2] We choose September of the year of leaving compulsory schooling since by this date those

the press and amongst politicians in recent years about pupils who persistently miss school due to unauthorised absence (truancy), which has, in several high profile cases, led to fines for parents.[3] Pupils who miss schooling because of truancy are likely to have lower test scores than pupils who do not miss school. When truancy reaches high levels then truants are more like high school dropouts, a phenomenon that has received a lot of attention in the US and Europe. However, it is not clear whether truancy has a direct effect on the risk of unemployment or NEET. A higher propensity to truant could increase the probability of unemployment or NEET insofar as it could act as a negative productivity signal to employers and training providers, providing of course that employers actually receive this signal. There is no guarantee that pupils would provide evidence of truancy from school during the job selection process. Moreover, it could be the case that young people who have truanted, search more intensively for jobs because they have 'switched off' school and want to work. Nevertheless, if truancy does lead to lower test scores, then there is a possible indirect, and positive, effect of truancy on the risk of unemployment or NEET. In contrast, there is a large literature which demonstrates a strong link between low high school test scores and a higher probability of unemployment and NEET (see Section 2).

We argue that because decisions regarding truancy, which could be seen as a proxy for effort at school, and performance in tests affect the subsequent transition from school, then these behavioural outcomes (decisions) are simultaneously

who intend to go to college, enter an apprenticeship/training scheme or take up employment will have done so.

[3]For instance, the BBC reported recently on the outcome of a court case in which a school had fined a parent for taking their child out of school to go on holiday, classed as unauthorised absence. The parent had challenged the fine but lost the case (see www.bbc.co.uk/news/education-39504338). Whilst this is an unusual case it does illustrate the steps that schools are now taking to reduce truancy.

determined. To capture this simultaneity a three equation model is estimated in which we allow for correlation between models for truancy, test scores, both of which are ordered categorical variables, and unemployment (or NEET), which are binary variables. Our model is not a full blown structural model since labour market behaviour may also be affected by attitudes to school that started early on in the education process which we are unable to model. However, we regard the interdependencies that we do uncover between truancy, test scores and labour market outcomes as important in shedding some light on causal mechanisms.

To estimate our model we use pupil level data from the Youth Cohort Studies (YCS), specifically YCS6 to YCS12, which cover the period of the late 1990s and early 2000s. To each of these datasets we append detailed information on the characteristics of the school attended which was obtained from the School Performance Tables and Schools Census.

The findings from our preferred model (heterogeneous model 2) suggest that truancy works through test scores (i.e. an indirect effect) rather than having a direct effect on labour market outcomes. However, truancy also has an unobserved effect on the risk of unemployment and the risk of NEET insofar as the correlation between latent variables for truancy and labour market outcomes are positive and statistically significant. Test scores have a direct effect on labour market outcomes, and through the estimation of ATTs, we show a good performance in high stakes tests (i.e. GCSEs) can mitigate the effect of truanting from school on labour market outcomes. In sum, truancy is not a significant problem for young people in terms of their post-school outcomes so long as this behaviour does not reduce test score performance. This makes sense insofar as employers observe test score performance in the job/training selection process whereas they are less likely to observe truancy behaviour. We find no evidence of 'reverse causality' i.e. that test scores determine truancy. We draw out the implications for policy in our conclusions.

The closest paper to ours from a methodological perspective is that by Buscha et al (2013) who estimate a bivariate ordered probit model of truancy and test scores, and allow for correlation between the unobservables of each outcome. Our paper contributes to the literature in several ways. First, we estimate a trivariate model, where the responses of primary interest are the risk of unemployment and NEET, however, we also modelling their interaction with test scores and truancy. Second, we investigate the direction of 'causation' between truancy and test scores which is ignored in previous work. Third, we have a richer set of covariates than Buscha et al (2103) because we map detailed school level data on to the pupil level YCS data - this allows us to tackle the issue of identification of each sub-model directly.[4]

The remainder of the paper is structured as follows. In section 2 we briefly discuss the existing literature on the determinants of test scores, truancy and unemployment or NEET. This is followed by the specification of our simultaneous model - a trivariate ordered probit model. Section 4 provides a discussion of the data that is used in our econometric analysis, and in Section 5 we present our results. This is followed by our conclusions.

[4]Dustman, Rajah and Soest (1998) and Daganais, Montmarquette and Viennot-Briot (2001) also estimate a system of equations, including test scores, however, their focus is upon the effect of part time work on this and the school-to-work transition.

2 A review of the literature

There is a large literature which investigates the determinants of the school-to-work transition, including the risk of unemployment and NEET (see Bradley and Nguyen, 2004 for a review of the early literature). Many of these papers estimate single equation models, often reduced form, where the role of test scores features prominently as a determinant of a successful school-to-work transition (Lynch, 1987; Andrews and Bradley, 1997; Crawford, Duckworth, Vignoles and Wyness, 2010; Duckworth and Schoon, 2010). Coles, Godfrey, Keung, Parratt and Bradshaw (2010) argue that the main determinants of NEET occur pre-school leaving and refer to different forms of 'educational disaffection and educational disadvantage'. Emrisch et al (2012) go further and argue that low test scores is a key mechanism that perpetuates disadvantage across the generations. Duncan et al (2012) also suggest that it is test scores in mathematics that is of primary importance for this 'intergenerational transmission of advantage.'

It is also worth noting that Coles et al (2010) see a direct correlation between educational disaffection and the probability of NEET. This is important in our context because educational disaffection refers to involuntary exclusion from school as well as what they refer to as 'self-exclusion' - truanting from school. Duckworth and Schoon (2010) also find this effect.

School effects on the school-to-work transition have also been identified over and above poor test scores and truancy behaviour. For instance, the type of school that a pupil attends also matters insofar as those pupils who attend a highly selective independent or grammar school are more likely to stay on (Micklewright 1989; Rice 1987 and 1999; Dolton et al 1999).

Gender and ethnic differences are also evident in that non-white girls are more likely to stay on beyond compulsory school leaving age to avoid unemployment (Leslie and Drinkwater, 1999) and this effect is greater for Indian and Chinese pupils than for Black Caribbeans (Bradley and Taylor, 2002).

Not surprisingly, the probability of staying on at school, and hence avoiding unemployment or NEET, is higher for young people from a professional family background, and much lower if their father is a manual worker (Rice 1987, 1999, Crawford, Duckworth, Vignoles and Wyness, 2011). Young people from single parent families and those with unemployed heads of household also tend to leave school early, partly because of financial constraints on the household and enter NEET (Coles et al, 2010). Duckworth and Schoon (2010) show using a number of datasets, that having parents with low education and living in social housing increases the likelihood of NEET. However, this finding applies to pupils from the British Cohort Survey dataset, which refers to pupils leaving school in the mid 1970s, but not the LSYPE dataset, which covers pupils who left school in the 1990s, suggesting some degree of educational mobility in more recent years.

In terms of the determinants of test scores and truancy, many studies have shown that a similar set of variables influence these outcomes. Family background is of prime importance as a determinant of test scores (Hanushek, 1986; 1992). Dustmann, Rajah and Soest (1998) distinguish between financial and time resources allocated to the child. Financial resources enable parents to choose better schools for their child, and provide a more suitable environment for studying, whereas time resources are related to the help given in explaining homework, for instance. These effects are often proxied by a wide range of parental and household variables, which also affect truancy behaviour. There are clear differences in the effect of parental occupation on test scores and truancy (Feinstein and Symons, 1999; Bosworth, 1994; Ermisch and Francesconi, 1997; Fuchs and Wossman 2004). Pupils with parents in professional occupations, for instance, have higher test scores and a lower probability of truanting, whereas pupils whose parents are in manual occupations are significantly more likely to be absent from school. Experience of life in a single parent family reduces test scores and increases the probability of truanting (Bosworth, 1994; Ermisch and Francesconi, 2001; Robertson and Symons, 1996). The structure and state of the local labour market also play a part in determining test scores and truancy. For instance, McIntosh (1998) investigates the effect of labour market conditions on transitions into training and finds only a small effect, whereas expected returns to continued schooling and prior academic attainment are more important determinants.

In terms of school effects Steele, Vignoles and Jenkins (2007) estimate a multilevel simultaneous equation model to investigate the effect of a school's resources on pupil test scores. Both test scores and school resources are modelled as a bivariate response. The multilevel feature of their model arises because schools are nested within LEAs, and the random effects at school and LEA level are correlated in both test score and resource responses. They find evidence that their two measures of resources - expenditure per pupil and the pupil-teacher ratio, which captures average class size - are endogenous with respect to test score performance in science; the effects with respect to mathematics are only statistically significant at the 10% level. Gibbons and McNally (2013) provide a recent review of the evidence on the causal relationship between school resources, including class size, and test scores.

In sum, there is a considerable literature on the school-to-work transition and on the determinants of test scores, though there is less analysis of truancy behaviour and post-school outcomes. Few papers have analysed the determinants of the risk of NEET. Much of the existing literature finds that a similar set of covariates 'determine' the school-to-work transition and schooling outcomes which makes the identification of a system of equations more challenging. However, recent work has sought to advance the literature by estimating systems of equations, and it is in this context that the current paper should be seen.

3 Statistical methodology

3.1 The relationship between test scores, truancy and unemployment (NEET)

It is apparent from our review of the literature that few studies have examined the effects of test scores and truancy on the risk of youth unemployment or NEET in a simultaneous equations framework. In this section we discuss the possible relationships between these three variables.

Two effects of truancy on test scores can be identified. There is a *direct* effect, whereby repeated absence from school leads to the acquisition of less knowledge, culminating in lower test scores. Since we observe in the data the incidence and duration of truancy we can measure this effect on test scores. However, it is likely that truancy also reflects a latent, *unobservable*, negative attitude to schooling, such as a dislike of studying and of school discipline or school ethos. Moreover, whilst it is highly likely that truancy will reduce test scores, its effect on the risk of unemployment or NEET is ambiguous (see the Introduction). Truancy could be treated as negative signal of productivity, hence increasing the risk of unemployment and inactivity, or truants dislike of school could reflect a strong desire to work or train (see Mroz et al, 2007), leading to increased search effort and hence a lower of risk of unemployment or NEET. Nevertheless, truancy could still affect the risk of unemployment and NEET *indirectly* via its effect on test scores. As the literature review shows the effect of lower test scores on the risk of unemployment is well documented, less so with respect to the risk of NEET. Our modelling strategy attempts to identify these direct, indirect and unobserved effects on the risk of unemployment and NEET.

The data set we use in this analysis (see Section 4) contains 5 levels of school truancy (Y_t) at age 16 for student i at school, as follows:

Response Y_{ti}	Description	Endogenous Y_{ti}^k
1	never truant	k =1
2	odd days	k =2
3	particular days	k =2
4	several days	k =3
5	week at a time	k =3

Truancy from school is a self-reported. The nature of Y_{ti} suggests we treat it as an ordered response with 5 categories. We treat truancy as an endogenous variable in the linear predictors for the models for test scores at age 16 (Y_{ei}) and subsequent unemployment and NEET (Y_{ni}) models. To simplify the joint estimation of endogenous truancy effects and correlation in the random effects of these other responses we use a reduced number of dummy variables in the linear predictors for Y_{ei}, and Y_{ni} , these are defined by the column headed Y_{ti}^k in the above table. Fo example, $Y_{ti}^2 = 1$, if $Y_{ti} = 2$, *or* 3 and 0 otherwise, with Y_{ti}^1 taken as the reference category.

In the UK a pupil's performance at school is typically measured by the level of attainment in public examinations. In this paper test scores refer to the number of, and grade in, the General Certificate of Secondary Education (GCSE) which is classified into one of six levels l of educational attainment at age 16 (Y_e), these are as follows:

Response Y_{ei}	Description	Endogenous Y_{ei}^l
1	no GCSEs	l =1
2	1-4, D-G, GCSEs	l =1
3	5+, D-G, GCSEs	l =2
4	1-4, A-C, GCSEs	l =3
5	5-9, A-C, GCSEs	l =4
6	10+, A-C, GCSEs	l =4

The nature of Y_{ei} suggests that we treat it as an ordered response with 6 categories. To simplify the joint estimation of endogenous GCSE effects and correlation in the random effects of the other responses we also use a reduced number of dummy variables for GCSE effects in the linear predictors for Y_{ni} . We define these in the column headed Y_{ei}^l in the above table. So, for example, $Y_{ei}^2 = 1$, if $Y_{ei} = 3$ and 0 otherwise, with Y_{ei}^1 taken as the reference category.

In this analysis we will use 2 levels of response for post 16 labour market outcomes (Y_n) at age 16 for individual i, as follows:

Response Y_{ni}	Description
1	education, employment or training
2	unemployed or NEET

The nature of Y_{ni} means we can treat it as an ordered response with just 2 categories (binary). Clearly, we do not treat labour market outcomes as an endogenous variable in the models for truancy and educational attainment.

There are various joint models that can be used for trivariate ordered responses, the most widely used assumes that observed responses (Y_{ti}, Y_{ei}, Y_{ni}) are obtained from underlying normally distributed variables $(Y_{ti}^*, Y_{ei}^*, Y_{ni}^*)$. The continuous latent variables e.g. Y_{ti}^* are observed in one of the (in this case $K = 5$) categories through a censoring mechanism, that is

$$
\begin{aligned}
Y_{ti} &= 1 \text{ if } c_{t0} < Y_{ti}^* \leq c_{t1} \\
&= 2 \text{ if } c_{t1} < Y_{ti}^* \leq c_{t2} \\
&= 3 \text{ if } c_{t2} < Y_{ti}^* \leq c_{t3} \\
&= 4 \text{ if } c_{t3} < Y_{ti}^* \leq c_{t4} \\
&= 5 \text{ if } c_{t5} < Y_{ti}^* \leq c_{t6}
\end{aligned}
$$

where the c_{tk}, $k = 1, ..., 5$ are finite cut points or thresholds of the latent variable Y_{ti}^*, with $c_{t0} = -\infty$, and $c_{t6} = \infty$. In this paper we assume that the cut points (c_{tk}, c_{el}, c_{nm}) don't vary across individuals (i). Ordered responses based on latent variables can be can be given a utility maximization interpretation, see Bhat and Pulugurta (1998).

The general specification of the latent variables $(Y_{ti}^{*}, Y_{ei}^{*}, Y_{ni}^{*})$ is as follows:

$$\begin{aligned}
Y_{ti}^{*} &= \beta_{1t}'(\mathbf{Family}_i, \mathbf{Personal}_i, \mathbf{School}_i, \mathbf{Place}_i, \overline{TR_{si}}, \overline{TR_{li}}) + \epsilon_{ti} \qquad (1)\\
&= \eta_{ti} + \epsilon_{ti}\\
Y_{ei}^{*} &= \beta_{1e}'(\mathbf{Family}_i, \mathbf{Personal}_i, \mathbf{School}_i, \mathbf{Place}_i) + \textstyle\sum_{k=2}^{k=3}\gamma_{ek}Y_{ti}^{k} + \epsilon_{ei} \qquad (2)\\
&= \eta_{ei} + \textstyle\sum_{k=2}^{k=3}\gamma_{ek}Y_{ti}^{k} + \epsilon_{ei},\\
Y_{ni}^{*} &= \beta_{1n}'(\mathbf{Family}_i, \mathbf{Personal}_i, \mathbf{School}_i, \mathbf{Place}_i) + \textstyle\sum_{k=2}^{k=3}\gamma_{nk}Y_{ti}^{k} + \sum_{l=2}^{l=4}\theta_{nl}Y_{ei}^{l} + \epsilon_{ni} \qquad (3)\\
&= \eta_{ni} + \textstyle\sum_{k=2}^{k=3}\gamma_{nk}Y_{ti}^{k} + \sum_{l=2}^{l=4}\theta_{nl}Y_{ei}^{l} + \epsilon_{ui}
\end{aligned}$$

where $(\epsilon_{ti}, \epsilon_{ei}, \epsilon_{ni})$ are from a trivariate standard normal distribution with correlation matrix Σ_{tel}, implying that the observed responses (Y_{ti}, Y_{ei}, Y_{ni}) are from a trivariate ordered probit model. We have used η_{si} to represent the linear predictors, $(s = t, e, n)$ of the exogenous covariates $(\mathbf{Family}_i, \mathbf{Personal}_i, \mathbf{School}_i, \mathbf{Place}_i)$. The linear predictors do not contain constants as these are not identified.

Identifiability in structural equation models with discrete outcomes has been widely discussed. Wilde (2000) notes that identifying variables are not needed in discrete response models if, for example, we are interested in the impact of the actual truancy Y_{ti}^{k} level, or outcome on Y_{ei}^{*} and Y_{ni}^{*}, and similarly with the actual GCSE Y_{ei}^{l} level or outcome on Y_{ni}^{*}. We do however have some identifying variables for Y_{ti}^{*} in η_{ei} and η_{ni}.

These identifying variables in Y_{ti}^{*} are are mean level of truancy in the school, excluding pupil i, $\left(\overline{TR_{si}}\right)$. $\overline{TR_{si}}$ captures a peer effect where it is expected that a higher average level of truancy will encourage similar behaviour for pupil i.

Similarly, we also include in the truancy model the average level of truancy in the local authority district in which the pupil lives $\overline{TR_{li}}$, to capture the potential effect of a neighbourhood peer effect.

The inclusion of $\left(\overline{TR_{si}}, \overline{TR_{li}}\right)$ gives us the opportunity to separate out the role of both the latent variable Y_{ti}^{*} and the observed categories of Y_{ti}^{k} in the test score model Y_{ei}^{*} (see Heckman, 1982).[5]. We expect that higher levels of truanting will lead to lower test scores. However, there is a potential problem of reciprocal causality insofar as Y_{ei} could also determine Y_{ti}. This could arise if pupils who systematically fail at school eventually reduces effort and start to truant. This is plausible given the 'teaching to test' that has arisen since the introduction of school league tables in 1988. However, we argue that this reverse causality should be less of an issue in our data for two reasons. First, our measure of test score is a summative statement of performance measured primarily at the end of compulsory schooling at age 16 when pupils sit for their GCSE exams, whereas our measure of truancy refers to behaviour between the ages of 14 and 16. Second, it is more likely that poor performance in coursework could increase the incidence of truancy because this does contribute to final GCSE grades. But, performance in tests in GCSE subjects is still weighted heavily and this implies that truancy behaviour will therefore affect overall performance in GCSE exams at age 16. Nevertheless, we do investigate the issue of the direction of causation between Y_{ti} and Y_{ei} in our modelling. (For notational simplicity, we will drop the i subscript in much of the following algebra if it is obvious that it applies, actually this isn't often, and we might as well include it)

[5] This contrasts with the approach taken by Buscha et al (2013) who include a latent variable for truancy.

Equations 1-3 are estimated initially as univariate models (referred to as the Homogenous model). However, as suggested earlier there are likely to be unobserved effects that determine truancy, test scores and the transition from school, such as attitudes to school discipline, ethos and motivation, as suggested earlier. These unobserved effects may bias the estimates of the variables of interest - truancy and test scores. Therefore, to disentangle the observable direct and indirect effects from the unobservable effect requires the simultaneous estimation of Equations 1-3 where test scores and truancy are treated as endogenous variables in our models of the risk of unemployment and NEET. In this model we also allow for correlation between the stochastic errors associated with Equations 1-3 (hereafter referred to as heterogeneous models).

Model 1 is our base model since the effects of truancy and test scores in Equations 1-3 are consistent with the existing literature, albeit that much of the literature only estimate univariate models. We also explore several other simultaneous models given our concerns about the direction of the underlying causal mechanisms. In model 2 we drop the direct effect of truancy on youth unemployment (and NEET), which means that the impact of truancy behaviour at school on labour market outcomes is picked up via its effect on test scores (the indirect effect) and through the unobserved effects. Model 3 drops the unobserved effect in the truancy equation. By dropping the direct effect of truancy on unemployment (and NEET) and the correlation between Equations 1 and 3 we can determine whether test scores play a more important role than truancy. Model 4 takes a different approach. In this model we re-introduce the direct effect of truancy in Equation 3 and the correlation between the errors in Equations 1 and 3, however, we explore the possibility of reverse causation between test scores and truancy.

Thus, although it is unlikely that test scores will affect truancy for the reasons cited above, Y_e is inserted in Equation 1 and Y_t is dropped from Equation 2.

The probabilities of the observed responses (Y_{ti}, Y_{ei}, Y_{ni}) are given by a triple integral which does not have a closed form, so for example if $Y_{ti} = 2, Y_{ei} = 3, Y_{ni} = 2$ then this individual's contribution to the likelihood is given by

$$\begin{aligned} L_i &= \Pr\left[Y_{ti} = 2, Y_{ei} = 3, Y_{ni} = 2\right] \\ &= \int_{c_{t1}-\eta_{ti}}^{c_{t2}-\eta_{ti}} \int_{c_{e2}-\eta_{ei}-\gamma_{e2}}^{c_{e3}-\eta_{ei}-\gamma_{e2}} \int_{c_{n11}-\eta_{ni}-\gamma 2-\theta_{n3}}^{c_{n2}-\eta_{ni}-\gamma_{n2}-\theta_{n3}} \phi\left(\epsilon_t, \epsilon_e, \epsilon_n; \Sigma_{ten}\right) d\epsilon_t d\epsilon_e d\epsilon_n. \end{aligned}$$

where $\phi\left(\epsilon_t, \epsilon_e, \epsilon_n; \Sigma_{ten}\right)$ is a trivariate standard normal density function with the 3×3 correlation matrix Σ_{ten}. The log likelihood for all individuals is then

$$\log L = \sum_{i=1} \log L_i \tag{4}$$

The log likelihood is maximized to provide the parameter estimates, this was done using CMP in Stata 14, Roodman (2009).

3.2 Measuring the average treatment effect on the treated

The average treatment effect on the treated (ATT) can help the interpretation of trivariate ordered response models with endogenous dummy variables. In our case the different levels of test scores $\left(Y_{ei}^{l}\right)$ and truancy $\left(Y_{ti}^{k}\right)$ are different treatment effects for unemployment and NEET (Y_{ni}). To obtain the treatment effects we need the joint model for the various observable treatments (Y_{ti}, Y_{ei}) and the unobservable counterfactual treatments for the same unemployment response, this is given by setting the parameters for the endogenous effects $(\gamma_{nk}, \theta_{nl})$ to zero. For our example, with $Y_{ti}=2, Y_{ei}=3, Y_{ni}=2$ we have:

$$\begin{aligned}&\Pr\left[Y_{ti}=2, Y_{ei}=3, Y_{ni}=2 \mid \gamma_{n2}=0, \theta_{n3}=0\right]\\ &=\int_{c_{t1}-\eta_t}^{c_{t2}-\eta_t}\int_{c_{e2}-\eta_e-\gamma_{e2}}^{c_{e3}-\eta_e-\gamma_{e2}}\int_{c_{n11}-\eta_n}^{c_{n2}-\eta_n}\phi\left(\epsilon_t,\epsilon_e,\epsilon_n;\Sigma_{ten}\right)d\epsilon_t d\epsilon_e d\epsilon_n.\end{aligned}$$

The joint probability of the (Y_{tki}, Y_{tli}) treatment is:

$$\begin{aligned}&\Pr\left[Y_{ti}=2, Y_{ei}=3\right]\\ &=\int_{c_{t1}-\eta_t}^{c_{t2}-\eta_t}\int_{c_{e2}-\eta_e-\gamma_{e2}}^{c_3-\eta_e-\gamma_{e2}}\phi\left(\epsilon_t,\epsilon_e,;\Sigma_{te}\right)d\epsilon_t d\epsilon_e.\end{aligned}$$

where Σ_{te} is the 2×2 correlation matrix for (ϵ_t, ϵ_e). The treatment effect on the treated, i.e. when $Y_{ti}=2$,and $Y_{ei}=3$, for individual i is

$$TT_{23i}=\frac{\Pr\left[Y_{ti}=2, Y_{ei}=3, Y_{ni}=2\right]-\Pr\left[Y_{ti}=2, Y_{ei}=3, Y_{ni}=2 \mid \gamma_{nk}=0, \theta_{nl}=0\right]}{\Pr\left[Y_{ti}=2, Y_{ei}=3\right]}$$

This estimate of the treatment effect varies by individual (i) because the exogenous covariates vary with i. The sample average of the treatment effects (e.g. when $Y_{ti}=2$,and $Y_{ei}=3$) gives the average treatment effect for unemployment or NEET (Y_n) on the treated (in this example ATT_{23}). The reference groups for the endogenous dummy variables are Y_{ti}^1, Y_{ei}^1 and Y_{ei}^2, so $ATT_{11}=ATT_{12}=0$.

4 The data

The data used in the following analysis has been obtained from several sources. First, pupil level data is extracted from the Youth Cohort Study (YCS) for England and Wales, which refers to Cohorts 6-12, covering the time period 1989-90 to

2000-01. The YCS is a nationally representative sample of 16-19 year olds, and in this particular case refers to pupils who were eligible to leave compulsory schooling in June of each year. The YCS contains detailed information on the young person's family background, personal characteristics as well as their propensity to truant, their test scores in GCSE subjects and their destination post-school, that is, whether they are employed, unemployed, in training or further education, or whether they are economically inactive. The latter is an heterogenous group including those young people who are caring for family members, for instance. We regard the NEET group as a joint category for the economically inactive and unemployed young people.

Second, we map information about the school each pupil attends from the School Performance Tables and the School Census, obtained from the Department for Education and Skills (DfES). The School Performance Tables contain information about the type of school, the number of pupils and the gender composition, whereas the Schools Census provides additional information on the proportion of qualified teachers, support staff hours and the proportion of pupils on free school meals. From this data we are able to construct measures of school background and quality, as well as the pupil's peer group.

The dataset also contains information on truancy at school, test score and labour market outcomes for nearly 70,000 young people, which is a major strength of these data when compared to other survey-based datasets.

Test scores are recorded for all of the GCSE subjects that a young person studies, not all of which are eventually examined, and graded from 'non-exam/fail' to 'A*'. We combine the grade and number of GCSE subjects studied to form an ordinal scale of test scores, and our classification system has the advantage that it covers the full range of the ability distribution, including the category '5 or more GCSE grades A* to C'. At the pupil level this is a very important threshold because performance at this level, in addition to successful study at A Level, permits entry to University, whereas at a school level the higher the proportion achieving in this category or better the more 'successful' the school is deemed to be. The propensity of a pupil to truant is measured on an ordinal scale ranging from 'never truant' to 'truants for weeks at a time'. Table 1 shows the relationship between the frequency of truancy and test scores for males and females separately. There is an almost monotonic increase in the level of test score performance as the frequency of truancy decreases and there appears to be a significant break in this relationship between 'Particular days' and 'Several days'. For instance, in the latter case the probability of no or low test scores increases quite substantially. In general, Table 1 does suggest a very clear negative relationship between the frequency of truancy and test scores - higher truancy is associated with lower test scores.

Table 2 shows the relationship between the frequency of truancy and labour market status, whereas Table 3 shows the equivalent for test scores. The risk of unemployment or NEET doubles as the frequency of truancy increases, except that is for females at the upper most part of truancy distribution where the rate of increase slows. The risk of unemployment and NEET differs between males and females, and is almost always greater for males. For instance, for those pupils who truant for weeks at a time the risk of unemployment and NEET is 6 percentage points and 5 percentage points higher for males, respectively. Table 3 also shows a clear negative relationship between the level of test scores and the risk of unemployment and NEET. In fact, these risks fall close to zero for the very highly qualified simply because they have more options after leaving school, such as college or employment. This is not the case for the unqualified where the risk of unemployment or NEET after leaving school is between 20-33 percent.

Tables 4 and 5 investigate the relationships between the frequency of truancy and test scores, holding labour market status constant for females and males separately. Panels A and B report the risk of unemployment (Panel B) and for non-unemployment (Panel A) where the risks are calculated row-wise implying a direct relationship between truancy and test scores. Panels C and D include the economically inactive along with the unemployed so giving the risk of NEET (Panel D) and non-NEET (Panel C). The pattern of risks now differs when compared to those reported in Tables 2 and 3. For instance, the risk of unemployment for the unqualified who have never truanted is 7% for females (Table 4) and 10% for males (Table 5) as compared with 1.4% and 2.2% in Table 2, but much lower than the risks in Table 3. At the opposite end of the scale unqualified females who truant for weeks at a time have a risk of unemployment of 64% and a risk of NEET of 61% which are far higher than those reported in Tables 2 and 3 for the two-way cross-tabulations. The corresponding figures for males are slightly higher - 67% and 63%. Moving up the test score distribution in Tables 4 and 5 (Panels B and D) shows that there is wider variation in the performance in terms of the risk of unemployment and NEET than is implied by estimates in Table 3 simply because of the additional effect of truancy behaviour on those risks. For instance, for males and females the average risk of unemployment for individuals with 5-9 GCSE grades A*-C is around 1% and approximately 3% for the risk of NEET. However, Table 4 shows that for females the (row-wise) risk of unemployment ranges 2% to 3% depending on whether the individual had never truanted when compared to those who truanted for weeks at a time. For the risk of NEET the corresponding figures are 33% and 3%. Similar findings are observed for males. These findings suggest that the relationship between truancy, test scores and labour market status are complex, insofar as doing well in tests, such as GCSEs, does mitigate some of the effect of excessive truanting insofar as the risk of unemployment and NEET decreases.

The analysis has been carried out for males and females separately. Appendix A, Table A1, contains the sample proportions for the explanatory variables used in the statistical models.

5 Econometric results

The determinants of truancy and test scores

The main focus of this paper is on the effects of test scores and truancy on the probability of unemployment or NEET several months after leaving school. However, given that we estimate a system of equations it is important to briefly assess the sub-models for truancy and test scores and to check whether these parts of the model are identified.

Table 6 focuses on the determinants of truancy and for brevity we report only the effects of the school level of truancy (minus that of the individual pupil), *truan*, which can be regarded as a peer effect, and a neighbourhood peer effect, *truand*. Panels A-D show the effects by gender and by outcome - NEET and unemployment. The effect of *truan* is remarkably similar in magnitude in almost all models, the exception being model 4, and is positive and statistically significant suggesting that pupils in schools with a higher rate of truancy are more likely to truant themselves. In contrast, the effect of *truand* differs by gender but is of a similar magnitude for unemployment and NEET outcomes. For males it is the case that pupils in neighbourhoods (in our case Local Authority districts) with a higher incidence of trauncy are themselves more likely to truant. The fact that at least one of the two covariates - truan and truand - are statistically significant suggests that the truancy sub-model is identified. In model 4 we include our test score variable to investigate whether test score performance affects truancy i.e. causality runs in the opposite direction. In general, our findings are statistically significant and suggest that pupils who (ultimately) achieve higher test scores are less likely to truant. However, it is also the case that these results are less robust for males where at least half of the estimates on our test score variable are statistically insignificant at conventional levels.

Table 7 reports the effects of truancy on test scores for males/females according to the various NEET/unemployment outcomes. Table 7 shows that the endogenous truancy indicators on test scores change from negative to positive when we allow for a correlation in the errors of truancy and test scores, i.e. in models 1, 2 and 3. This feature of these models may seem counter-intuitive, however, the correlation is large and negative (of order -0.5) for these heterogenous models, see Table 8. It is likely that the overall interdependency between truancy and test scores will still be negative in heterogenous models 1, 2 and 3. The positive direct effects of the endogenous truancy indicators are not large enough to dominate the large negative correlation in the errors for all cells of these models. Table 1 suggests that we might expect a negative relationship between truancy and test scores in the male and female data.

5.1 The effects of test scores and truancy on the risk of unemployment and NEET

Tables 8a to 8d show the estimated effects of truancy and test scores on the probability of a young person becoming unemployed or entering the NEET category several months after leaving school. The estimated effects for the homogenous model are fairly standard findings in the cross sectional literature. Higher levels truancy increase the probability of unemployment and NEET for both males and females. Conversely, the higher the pupils test scores the lower the likelihood of unemployment and NEET probably because these pupils have more choices after leaving compulsory schooling insofar as they can continue their education, enter a training programme or get a job. These effects can be regarded as direct effects of truancy and test scores on labour market outcomes. However, recall that truancy reduces test scores and so there is also an additional indirect effect of truancy on the probability of a young people becoming unemployed or NEET. The total effect of truancy on labour market outcomes would therefore be underestimated by simply looking at the direct effect.

Of course these homogenous models do not take account of the effect of unobservables, such as motivation, or the correlations in the latent variables of truancy, GCSE and unemployment. Tables 8a to 8d therefore also report the estimated effects of truancy and test scores on youth unemployment and NEET from various heterogeneous (trivariate ordered probit) models. For males the effect of test scores remains negative and statistically significant, however, the estimated effects from the heterogeneous models are roughly twice as large in absolute magnitude when compared to those from the homogenous models. Similar effects are observed for females. Thus we argue that, when compared to cross-sectional models that do not allow for the interdependencies between test scores and truancy, higher test scores have an even greater negative effect on the risk of entering unemployment or NEET on leaving school. The story is not so simple with respect to the estimated effects of truancy. In model 1 the estimated effects of truancy on unemployment and NEET becomes negative and statistically insignificant for males, however, they are statistically significant for females which seems implausible. For males the story with regard to truancy is consistent across all heterogenous models. Thus, focussing on model 1 it could be argued that female pupils who are 'turned off' by school, and hence truant more, also search more intensively for work and hence avoid unemployment and NEET. However, in model 3 and model 4 (unemployment only) the estimated effects of truancy become positive and statistically significant again, and with regard to the risk of unemployment (Panel B) the effect of truancy is larger when compared with the homogenous models. Our findings for truancy are therefore less robust than those for test scores and depend on the correlation structure that one assumes between test scores, truancy and labour market outcomes.[6]

Tables 8a to 8d reports the correlations between the errors in the various branches of the model, and pick up the effect of unobservable differences between pupils e.g. differences in motivation. We compare the heterogenous models 1-4 where panels A and C report the results for the NEET outcome for females and males, respectively, and panels B and D show the equivalent results for the unemployment outcome. What is clear when one compares the results for NEET and

[6]We also estimated a model with interaction effects between Ye and Yt, which are available on request. Many of the interaction terms are statistically insignificant, which suggests that the main effects of Ye and Yt are sufficient.

unemployment outcomes for each gender is that there are only small differences in the estimated correlations. We therefore focus on the NEET outcome.

Tables 8a to 8d shows that there are some differences in the absolute values of the estimated correlations for each pairwise comparison of the sub-branches of the heterogeneous models, even though the pattern of correlations is similar across models 1-4 for each gender group. Model 1 is where there are greater differences in the correlations between males and females where the effects for females are much greater. Thus for model 1 the correlations suggest that there is a negative and statistically significant correlation between the unobserved effects on truancy and test score sub-models for females (see Rho_{te}). Pupils who are unobservably more likely to truant, perhaps because they are demotivated by school, are also unobservably less able and so their test scores are lower. This effect is almost identical in terms of magnitude for models 2 and 3 but is halved in model 4 when interaction effects between observed truancy and exam scores are included. A very similar story emerges for males. These findings suggest that there is indeed an indirect effect of truancy on NEET. With regard to the correlations between unobservables for the truancy and NEET models (see Rho_{tn}), the estimates are positive and statistically significant, suggesting pupils who are unobservably more likely to truant are more likely to become unemployed or economically inactive. A lack of motivation at school translates into poor entry into the job market, possibly because of poor motivation to find a job or training place, or because employers are able to screen out such youngsters during the selection process. Again this result is consistent - see models 2 and 4 - and it is a similar story for males. Finally, we consider the correlations between the unobservables for exam scores and the probability of NEET (see Rho_{en}). There is some variation in the estimated effects between these models, the exception being model 3 where we exclude the random effect on truancy. In general, the correlations between the unobserved effects are negative and statistically significant. Unobservably more able students are less likely to become unemployed or economically inactive. The story for males is similar although the estimated correlations are smaller.

In summary, unobservables do matter, however, in terms of the magnitudes of the effects that we estimate, it is Rho_{tn} that has the larger effect.

Finally, it is necessary to discuss which of the various heterogenous models we prefer and why. There are several ways to do this. First, we can assess whether the direction of the main effects of truancy and test scores on unemployment and NEET outcomes are correct insofar as they are consistent with what one might expect based on theory and/or the previous literature. Second, we can compare models with respect to their log likelihoods and associated chi-square values, which gives us some insight into the goodness of fit of each heterogenous model.

In terms of the first comparison, Tables 8a to 8d show that heterogeneous model 2 appears to have the most plausible pattern of estimates insofar as the increased incidence of truancy increases the risk of NEET and unemployment, especially in the case of females where the estimated effects are statistically significant. For males the estimates on truancy are mis-signed with respect to the NEET outcome and statistically insignificant for both NEET and unemployment outcomes. However, the correlation between unobservables in the truancy and test score equations is (correctly) negatively signed and statistically significant. Similarly, model 2 shows that test scores have the right sign and pattern and are statistically significant for males and females and for both NEET and unemployment. The correlation between the unobservables in the test score and outcome equations are also statistically significant and correctly signed. The other heterogenous models do not perform as well as model 2. In terms of the second way of comparing models, the Table also shows that model 2 does not have the lowest log likelihood it is not significantly different to the other heterogeneous models, and as such is still a good fit to the data. A further comparison worth making is between the homogenous model and model 2, where one might ask the question about the value added of estimating the heterogenous model 2. Essentially, the key finding is that the estimates on the main effects of truancy and test scores are generally *over* estimated in the homogenous models presumably because no allowance is made for the effect of unobservables that are likely to be correlated with those observed effects. There is also the additional information provided by the correlations themselves.

5.2 Calculating the magnitude of the main effects of truancy and test scores

Recall that the model for labour market behaviour Yn is defined over a state space for destinations for unemployment, U, or NEET, N, each of which are compared with leaving school and entering employment. *The Average Treatment on the Treated (ATT)* for the unemployed is the probability of a flow into unemployment and is obtained by estimating a model where the test score variable is non-zero. We then estimate a model where the test score variable is set to zero and the ATT is the difference between the two. This is repeated for the NEET category. Note that for model 2, our preferred model, we set the direct effect of Truancy on U and N equal to zero, however, T does have an effect on unemployment (and NEET) though the indirect effects, e.g. on test scores and also through the correlations in the omitted effects of Truancy with respect to unemployment (and NEET). However, the ATT effects are only computed for the direct effects.

Table 9 and 10 report the estimated ATTs for the unemployment and NEET models, for males and females separately. There are differences in the ATT effects between these groups, however, it is clear that in all cases the effects of test scores and truancy are negative. The negative effects can be interpreted as follows: for a particular level of test score and truancy, and when compared with the control group, the negative effect reduces the risk of unemployment when compared to the base category, which implies that the effect of test score dominates the effect of truancy. We can therefore think of test score performance as compensating for poor attendance. This is best seen by looking at low levels of truancy (e.g. 2) where the compensating effect of test scores is modest, as expected because truancy at this level is not so much of a problem (e,g. the ATT for test scores=3 is -0.06 versus versus test scores=6 is-0.13), whereas for truancy=5 and test scores=3 the ATT is -0.12 versus an ATT of -0.27 where test scores=6. Note, however, that truancy also impacts indirectly via its effect on test scores and through the correlation in the errors. Nevertheless, it is still the case that the test score effect dominates the truancy effect in terms of labour market outcomes. Of course, this is not to deny that reducing truancy is important; it because reducing truancy is likely to improve individual test which in turn improves labour market prospects.

6 Conclusion

In this paper we investigate the effects of test scores and truancy behaviour on the labour market outcomes of teenagers in England and Wales. We also investigate the interdependencies, and implicitly the direction of causation, between truancy behaviour and test score performance. This is because it may be that truancy has a direct effect on the risk of unemployment or NEET amongst young people as well as an indirect effect via the effect of truancy on test scores. Our modelling approach reflects the idea that a young persons decisions regarding truancy, which could be seen as a proxy for effort at school, and performance in tests affect the subsequent transition from school, then these behavioural outcomes (decisions) are simultaneously determined. Consequently, to capture this simultaneity a three equation model was estimated in which we allow for correlation between models for truancy, test scores, both of which are ordered categorical variables, and unemployment (or NEET), which are binary variables. We also allow for correlations between the unobservable factors that drive truancy, test score and labour market outcomes, such as motivation. Several models are estimated which allow for different specifications of the relationships between the three outcome measures - truancy, test scores and labour market outcomes. To estimate our models we use detailed pupil and school level data from the Youth Cohort Studies (YCS), specifically YCS6 to YCS12, as well as school performance and school census data, which cover the period of the late 1990s and early 2000s.

The findings from our preferred model (heterogeneous model 2) suggest that truancy works through test scores (i.e. an indirect effect) rather than having a direct effect on labour market outcomes. However, truancy also has an unobserved effect on the risk of unemployment and the risk of NEET insofar as the correlation between latent variables for truancy and labour market outcomes are positive and statistically significant. Test scores have a direct effect on labour market outcomes, and through the estimation of ATTs, we show a good performance in high stakes tests (i.e. GCSEs) can mitigate the effect of truanting from school on labour market outcomes. In sum, truancy is not a significant problem for young people in terms of their post-school outcomes so long as this behaviour does not reduce test score performance. This makes sense insofar as employers observe test score performance in the job/training selection process whereas they are less likely to observe truancy behaviour.

Thus the popular view that truancy is universally bad for young people is open to question according to our findings. The story is more complex and it is important to simultaneously track academic performance rather than focus in on truancy per se. This is not to say that the government, schools, and parents should ignore truancy behaviour; it matters where test score performance will be adversely affected because this will lead to poor labour market outcomes. We also expect that the determinants of truancy behaviour and its effect on academic performace, and hence test scores, goes back further into the educational careers of young people than we are able to control for. Nevertheless, our analysis of the latter part of the educational process between ages 14-16 has helped to shed some light on the complex interaction between truancy behaviour, test score performance and early labour market outcomes.

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Table 1 The relationship between pupil test scores and truancy

Males	*Test scores*						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.018	0.019	0.113	0.246	0.476	0.129	20327
Odd days	0.036	0.040	0.167	0.328	0.372	0.056	8371
Particular days	0.084	0.080	0.236	0.362	0.215	0.024	1711
Several days	0.221	0.130	0.213	0.264	0.158	0.014	493
Weeks at a time	0.453	0.130	0.160	0.187	0.066	0.004	470
Total	1122	984	4284	8584	13261	3137	31372

Females	*Test scores*						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.012	0.014	0.069	0.222	0.489	0.194	22874
Odd days	0.022	0.022	0.106	0.333	0.418	0.099	11143
Particular days	0.058	0.062	0.171	0.405	0.271	0.032	2516
Several days	0.166	0.093	0.176	0.355	0.194	0.016	808
Weeks at a time	0.376	0.118	0.160	0.244	0.097	0.005	595
Total	1028	874	3411	10255	16732	5636	37936

Table 2 Truancy behaviour and labour market outcomes

	Females			Males		
	Risk of:			*Risk of:*		
Truancy	*Unemployment*	*NEET*	n	*Unemployment*	*NEET*	n
Never	0.014	0.035	22874	0.022	0.043	20327
Odd days	0.028	0.062	11143	0.044	0.070	8371
Particular days	0.072	0.126	2516	0.093	0.137	1711
Several days	0.140	0.209	808	0.136	0.176	493
Weeks at a time	0.180	0.277	595	0.255	0.328	470
Total	0.028	2147	37936	1161	1942	31372

Note: The proportions of unemployed and NEET pupils are computed relative to the non-unemployed categories and the non-NEET categories.

Table 3 Test scores and labour market outcomes

	Females			Males		
	Risk of:			*Risk of:*		
Test scores	*Unemployment*	*NEET*	n	*unemployment*	*NEET*	n
None	0.211	0.330	1028	0.210	0.260	1122
1-4D-G	0.136	0.193	874	0.149	0.189	984
5+ G-G	0.066	0.113	3411	0.071	0.103	4284
1-4 A*-C	0.034	0.068	10255	0.039	0.068	8584
5-9 A*-C	0.008	0.029	16732	0.009	0.029	13261
10+ A*-C	0.001	0.014	5636	0.004	0.018	3137
Total	0.028	0.057	37936	0.037	0.062	31372

Table 4 The relationship between truancy and test scores by labour market status, Females

Panel A: Non-unemployed

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.011	0.013	0.066	0.220	0.493	0.197	22546
Odd days	0.019	0.020	0.102	0.332	0.426	0.102	10826
Particular days	0.047	0.055	0.165	0.411	0.287	0.034	2335
Several days	0.122	0.082	0.181	0.376	0.220	0.019	695
Weeks at a time	0.320	0.121	0.180	0.260	0.113	0.006	488
Total	0.022	0.021	0.086	0.269	0.450	0.153	36890

Panel B: Unemployed

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.073	0.085	0.241	0.384	0.198	0.018	328
Odd days	0.123	0.107	0.240	0.385	0.142	0.003	317
Particular days	0.204	0.155	0.254	0.326	0.061	0.000	181
Several days	0.434	0.159	0.142	0.230	0.035	0.000	113
Weeks at a time	0.636	0.103	0.065	0.168	0.028	0.000	107
Total	0.207	0.114	0.214	0.336	0.122	0.007	1046

Panel C: Non-NEET

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.010	0.013	0.065	0.219	0.494	0.199	22067
Odd days	0.017	0.019	0.099	0.332	0.430	0.103	10455
Particular days	0.043	0.054	0.017	0.410	0.293	0.035	2198
Several days	0.111	0.080	0.178	0.390	0.224	0.017	639
Weeks at a time	0.286	0.128	0.186	0.272	0.123	0.005	430
Total	0.019	0.019	0.082	0.260	0.442	0.151	36789

Panel D: NEET

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.064	0.051	0.161	0.331	0.328	0.064	807
Odd days	0.103	0.073	0.206	0.352	0.237	0.029	688
Particular days	0.164	0.123	0.217	0.371	0.116	0.009	318
Several days	0.373	0.142	0.166	0.225	0.083	0.012	169
Weeks at a time	0.612	0.091	0.091	0.170	0.030	0.006	165
Total	0.158	0.079	0.179	0.323	0.225	0.036	2147

Table 5 The relationship between truancy and test scores by labour market status, Males

Panel A: Non-unemployed

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.016	0.017	0.109	0.244	0.483	0.131	19877
Odd days	0.031	0.036	0.161	0.328	0.385	0.059	8006
Particular days	0.069	0.069	0.231	0.371	0.233	0.026	1552
Several days	0.200	0.115	0.221	0.279	0.169	0.016	426
Weeks at a time	0.380	0.129	0.171	0.234	0.080	0.006	350
Total	0.029	0.028	0.132	0.273	0.435	0.104	30211

Panel B: Unemployed

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.098	0.082	0.293	0.347	0.160	0.020	450
Odd days	0.143	0.134	0.282	0.337	0.099	0.006	365
Particular days	0.226	0.189	0.277	0.270	0.038	0.000	159
Several days	0.358	0.224	0.164	0.164	0.090	0.000	67
Weeks at a time	0.667	0.133	0.125	0.050	0.025	0.000	120
Total	0.203	0.127	0.263	0.292	0.106	0.010	1161

Panel C: Non-NEET

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.015	0.017	0.108	0.242	0.484	0.132	19499
Odd days	0.031	0.036	0.161	0.328	0.386	0.059	7782
Particular days	0.065	0.067	0.234	0.372	0.234	0.027	1477
Several days	0.202	0.116	0.219	0.271	0.175	0.017	406
Weeks at a time	0.367	0.139	0.174	0.234	0.082	0.003	316
Total	0.028	0.027	0.131	0.272	0.438	0.105	29430

Panel D: NEET

	Test scores						
Truancy	None	1-4 D-G	5+ D-G	1-4 A*-C	5-9 A*-C	10+ A*-C	All
Never	0.067	0.060	0.232	0.319	0.271	0.050	878
Odd days	0.105	0.104	0.248	0.338	0.190	0.015	589
Particular days	0.201	0.162	0.244	0.295	0.094	0.004	234
Several days	0.310	0.195	0.184	0.230	0.081	0.000	87
Weeks at a time	0.630	0.110	0.130	0.091	0.033	0.007	154
Total	0.150	0.096	0.228	0.300	0.198	0.028	1942

Table 6 Ordered Probit Models of the Determinants of Truancy, Homogenous and Heterogenous

Panel A: NEET - Females

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heterogeneous - Model 3			Heterogeneous - Model 4		
Variable	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
truan	4.665	0.655	0.000	1.899	0.598	0.001	1.894	0.597	0.002	1.852	0.597	0.002	2.859	0.640	0.000
truand	-0.061	1.372	0.964	2.033	1.237	0.100	2.045	1.235	0.098	2.017	1.236	0.103	1.473	1.340	0.272
Ye3													-0.373	0.033	0.000
Ye4													-0.310	0.037	0.000
Ye56													-0.450	0.053	0.000
/cut1	0.242	0.087		0.233	0.086	0.006	0.234	0.085	0.006	0.225	0.086	0.009	-0.203	0.101	0.043
/cut2	1.281	0.087		1.270	0.086	0.000	1.271	0.086	0.000	1.263	0.086	0.000	0.864	0.099	0.000
/cut3	1.824	0.087		1.812	0.086	0.000	1.813	0.086	0.000	1.804	0.086	0.000	1.443	0.099	0.000
/cut4	2.201	0.088		2.193	0.087	0.000	2.195	0.087	0.000	2.185	0.087	0.000	1.856	0.098	0.000

Panel B: NEET - Males

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heterogeneous - Model 3			Heterogeneous - Model 4		
Variable	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
truan	4.298	0.725	0.000	2.158	0.674	0.001	2.122	0.676	0.002	2.067	0.675	0.002	2.830	0.708	0.000
truand	3.359	1.551	0.030	3.283	1.424	0.021	3.288	1.428	0.021	3.258	1.427	0.022	3.750	1.513	0.013
Ye3													-0.384	0.035	0.000
Ye4													-0.322	0.044	0.000
Ye56													-0.424	0.065	0.000
/cut1	0.586	0.098		0.576	0.096	0.000	0.567	0.097	0.000	0.553	0.097	0.000	0.181	0.115	0.115
/cut2	1.613	0.098		1.602	0.097	0.000	1.593	0.097	0.000	1.579	0.097	0.000	1.236	0.113	0.000
/cut3	2.133	0.099		2.121	0.097	0.000	2.112	0.098	0.000	2.098	0.098	0.000	1.790	0.112	0.000
/cut4	2.445	0.099		2.436	0.098	0.000	2.429	0.098	0.000	2.413	0.099	0.000	2.135	0.112	0.000

Panel C Unemployment, Females

Variable	Homogenous Estimate	s.e.	P-value	Heterogeneous - Model 1 Estimate	s.e.	P-value	Heterogeneous - Model 2 Estimate	s.e.	P-value	Heterogeneous - Model 3 Estimate	s.e.	P-value	Heterogeneous - Model 4 Estimate	s.e.	P-value
truan	4.665	0.655	0.000	2.859	0.640	0.000	1.774	0.597	0.003	1.807	0.598	0.003	2.732	0.641	0.000
truand	-0.061	1.372	0.964	1.473	1.340	0.272	2.219	1.236	0.073	2.114	1.238	0.088	1.649	1.344	0.220
Ye3													-0.372	0.033	0.000
Ye4													-0.307	0.037	0.000
Ye56													-0.446	0.053	0.000
/cut1	0.242	0.087		-0.203	0.101	0.043	0.225	0.086	0.009	0.225	0.086	0.009	-0.208	0.101	0.040
/cut2	1.281	0.087		0.864	0.099	0.000	1.262	0.086	0.000	1.263	0.086	0.000	0.859	0.099	0.000
/cut3	1.824	0.087		1.443	0.099	0.000	1.804	0.086	0.000	1.804	0.086	0.000	1.438	0.099	0.000
/cut4	2.201	0.088		1.856	0.098	0.000	2.185	0.087	0.000	2.185	0.087	0.000	1.851	0.099	0.000

Panel D Unemployment, Males

	Homogenous Estimate	s.e.	P-value	Heterogeneous - Model 1 Estimate	s.e.	P-value	Heterogeneous - Model 2 Estimate	s.e.	P-value	Heterogeneous - Model 3 Estimate	s.e.	P-value	Heterogeneous - Model 4 Estimate	s.e.	P-value
truan	4.298	0.725	0.000	2.099	0.676	0.002	2.091	0.676	0.002	2.075	1.429	0.020	2.767	0.710	0.000
truand	3.359	1.551	0.030	3.398	1.429	0.017	3.381	1.429	0.018	3.318	0.034	0.001	3.885	1.519	0.011
Ye3													-0.382	0.035	0.000
Ye4													-0.317	0.044	0.000
Ye56													-0.415	0.065	0.000
/cut1	0.586	0.098		0.557	0.097	0.000	0.557	0.097	0.000	0.554	0.097	0.000	0.169	0.115	0.141
/cut2	1.613	0.098		1.584	0.097	0.000	1.583	0.097	0.000	1.580	0.097	0.000	1.224	0.113	0.000
/cut3	2.133	0.099		2.102	0.098	0.000	2.102	0.098	0.000	2.099	0.098	0.000	1.778	0.112	0.000
/cut4	2.445	0.099		2.418	0.098	0.000	2.418	0.098	0.000	2.414	0.099	0.000	2.122	0.112	0.000

Table 7 Ordered Probit Models of the Truancy on Test Scores, Homogenous and Heterogeneous Models

Panel A NEET, Females

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heterogeneous - Model 3			Heterogeneous - Model 4		
Variable	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	-0.396	0.012	0.000	0.403	0.030	0.000	0.405	0.030	0.000	0.407	0.030	0.000	na		
Yt45	-1.390	0.030	0.000	0.208	0.066	0.001	0.213	0.065	0.001	0.207	0.065	0.001	na		
/cut1	-3.408	0.081		-2.720	0.088	0.000	-2.717	0.088	0.000	-2.701	0.087	0.000	-3.047	0.080	0.000
/cut2	-3.063	0.080		-2.413	0.086	0.000	-2.410	0.086	0.000	-2.395	0.086	0.000	-2.734	0.079	0.000
/cut3	-2.388	0.079		-1.810	0.083	0.000	-1.808	0.083	0.000	-1.793	0.083	0.000	-2.103	0.079	0.000
/cut4	-1.369	0.079		-0.896	0.081	0.000	-0.894	0.081	0.000	-0.880	0.080	0.000	-1.131	0.078	0.000
/cut5	0.144	0.079		0.485	0.078	0.000	0.487	0.078	0.000	0.497	0.078	0.000	0.335	0.078	0.000

Panel B NEET, Males

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heterogeneous - Model 3			Heterogeneous - Model 4		
Variable	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	-0.395	0.013	0.000	0.338	0.037	0.000	0.344	0.037	0.000	0.351	0.037	0.000	na		
Yt45	-1.408	0.036	0.000	0.033	0.080	0.681	0.044	0.080	0.585	0.047	0.079	0.554	na		
/cut1	-3.168	0.087		-2.693	0.094	0.000	-2.682	0.094	0.000	-2.657	0.093	0.000	-2.908	0.087	0.000
/cut2	-2.801	0.087		-2.358	0.092	0.000	-2.348	0.092	0.000	-2.324	0.092	0.000	-2.572	0.086	0.000
/cut3	-2.014	0.086		-1.640	0.089	0.000	-1.631	0.089	0.000	-1.608	0.089	0.000	-1.832	0.086	0.000
/cut4	-1.113	0.086		-0.809	0.087	0.000	-0.801	0.087	0.000	-0.780	0.087	0.000	-0.964	0.086	0.000
/cut5	0.466	0.086		0.670	0.086	0.000	0.676	0.086	0.000	0.693	0.085	0.000	0.577	0.085	0.000

Panel C Unemployment, Females

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heterogeneous - Model 3			Heterogeneous - Model 4		
	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	-0.396	0.012	0.000	0.405	0.030	0.000	0.406	0.030	0.000	0.405	0.030	0.000	na		
Yt45	-1.390	0.030	0.000	0.212	0.065	0.001	0.214	0.065	0.000	0.202	0.065	0.002	na		
/cut1	-3.408	0.081		-2.713	0.088	0.000	-2.712	0.088	0.000	-2.711	0.087	0.000	-3.043	0.080	0.000
/cut2	-3.063	0.080		-2.406	0.086	0.000	-2.405	0.086	0.000	-2.405	0.086	0.000	-2.730	0.079	0.000
/cut3	-2.388	0.079		-1.804	0.083	0.000	-1.803	0.083	0.000	-1.802	0.083	0.000	-2.100	0.079	0.000
/cut4	-1.369	0.079		-0.889	0.081	0.000	-0.889	0.081	0.000	-0.888	0.080	0.000	-1.127	0.078	0.000
/cut5	0.144	0.079		0.491	0.078	0.045	0.491	0.079	0.000	0.491	0.078	0.000	0.339	0.078	0.000

Panel D Unemployment, Males

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heterogeneous - Model 3			Heterogeneous - Model 4		
	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	-0.395	0.013	0.000	0.338	0.037	0.000	0.341	0.037	0.000	0.342	0.037	0.000	na		
Yt45	-1.408	0.036	0.000	0.034	0.080	0.420	0.039	0.080	0.628	0.033	0.079	0.680	na		
/cut1	-3.168	0.088		-2.687	0.094	0.000	-2.684	0.094	0.000	-2.677	0.093	0.000	-2.904	0.087	0.000
/cut2	-2.801	0.087		-2.352	0.092	0.000	-2.350	0.092	0.000	-2.343	0.092	0.000	-2.569	0.086	0.000
/cut3	-2.014	0.086		-1.634	0.089	0.000	-1.631	0.089	0.000	-1.625	0.089	0.000	-1.829	0.086	0.000
/cut4	-1.113	0.086		-0.804	0.087	0.000	-0.802	0.087	0.000	-0.796	0.087	0.000	-0.960	0.086	0.000
/cut5	0.466	0.086		0.676	0.086	0.000	0.677	0.086	0.000	0.680	0.085	0.000	0.580	0.085	0.000

Table 8a Ordered Probit Model- NEET, females

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heteterogeneous - Model 3			Heteterogeneous - Model 4		
Variable	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	0.248	0.024	0.000	-0.025	0.064	0.692							-0.040	0.066	0.545
Yt45	0.639	0.045	0.000	0.135	0.127	0.287							0.079	0.129	0.540
Ye3	-0.467	0.044	0.000	-0.418	0.049	0.000	-0.461	0.047	0.000	-0.665	0.043	0.000	-0.467	0.051	0.000
Ye4	-0.717	0.039	0.000	-0.624	0.061	0.000	-0.692	0.057	0.000	-1.054	0.045	0.000	-0.653	0.061	0.000
Ye56	-1.089	0.041	0.000	-0.914	0.093	0.000	-1.013	0.087	0.000	-1.679	0.065	0.000	-0.953	0.094	0.000
Rho_te				-0.511	0.017		-0.512	0.017		-0.517	0.017		-0.261	0.014	
Rho_tn				0.198	0.042		0.207	0.015		0.000	-		0.206	0.042	
Rho_en				-0.127	0.032		-0.107	0.027		0.141	0.019		-0.102	0.030	
LogL	-7235.992			-90884.24			-90889.801			-90988.150			-91027.132		
n	37936			37936			37936			37936			37936		

Table 8b Ordered Probit Models, Unemployment - females

	Homogenous model			Heterogeneous - Model 1			Heterogeneous - Model 2			Heteterogeneous - Model 3			Heteterogeneous - Model 4		
	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	0.241	0.033	0.000	-0.028	0.080								-0.046	0.082	0.574
Yt45	0.641	0.053	0.000	0.123	0.155								0.080	0.157	0.610
Ye3	-0.420	0.050	0.000	-0.396	0.061		-0.444	0.058	0.000	-0.663	0.049	0.000	-0.446	0.063	0.000
Ye4	-0.702	0.045	0.000	-0.657	0.084		-0.737	0.077	0.000	-1.137	0.053	0.000	-0.687	0.085	0.000
Ye56	-1.268	0.052	0.000	-1.178	0.137		-1.300	0.126	0.000	-2.047	0.083	0.000	-1.219	0.138	0.000
Rho_te				-0.512	0.017		-0.513	0.017		-0.514	0.017		-0.262	0.014	
Rho_tn				0.194	0.054		0.202	0.020		0.000	-		0.202	0.052	
Rho_en				-0.099	0.048		-0.071	0.041		0.207	0.024		-0.071	0.045	
LogL	-3902.169			-87555.58			-87558.97			-87607.479			-87699.457		
n	37936			37936			37936			37936			37936		

Table 8c Ordered Probit Model - NEET, males

	Homogenous			Heterogeneous - Model 1			Heterogeneous - Model 2			Heteterogeneous - Model 3			Heteterogeneous - Model 4		
Variable	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	0.179	0.025	0.000	-0.201	0.069	0.004							-0.235	0.071	0.001
Yt45	0.579	0.051	0.000	-0.177	0.142	0.213							-0.230	0.142	0.106
Ye3	-0.371	0.042	0.000	-0.382	0.050	0.000	-0.427	0.048	0.000	-0.598	0.042	0.000	-0.453	0.052	0.000
Ye4	-0.570	0.039	0.000	-0.590	0.066	0.000	-0.659	0.062	0.000	-0.955	0.049	0.000	-0.635	0.067	0.000
Ye56	-0.923	0.041	0.000	-0.940	0.101	0.000	-1.043	0.096	0.000	-1.562	0.071	0.000	-0.995	0.102	0.000
Rho_te				-0.464	0.022		-0.468	0.022		-0.475	0.021		-0.251	0.019	
Rho_tn				0.261	0.046		0.158	0.016		0.000	-		0.280	0.046	
Rho_en				-0.079	0.035		-0.019	0.031		0.175	0.022		-0.049	0.033	
LogL	-6552.801			-75419.04			-75427.575			-75475.124			-75503.407		
n	31372			31372			31372			31372			31372		

Table 8d Ordered Probit Models,Males, Unemploment, males

	Homogenous model			Heterogeneous - Model 1			Heterogeneous - Model 2			Heteterogeneous - Model 3			Heteterogeneous - Model 4		
	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value	Estimate	s.e.	P-value
Yt23	0.221	0.032	0.000	-0.101	0.083	0.221							-0.132	0.085	0.119
Yt45	0.597	0.056	0.000	-0.043	0.166	0.795							-0.091	0.167	0.584
Ye3	-0.414	0.046	0.000	-0.420	0.060	0.000	-0.461	0.057	0.000	-0.674	0.046	0.000	-0.485	0.063	0.000
Ye4	-0.669	0.044	0.000	-0.680	0.088	0.000	-0.747	0.080	0.000	-1.126	0.055	0.000	-0.725	0.088	0.000
Ye56	-1.221	0.051	0.000	-1.223	0.140	0.000	-1.326	0.130	0.000	-2.000	0.085	0.000	-1.282	0.141	0.000
Rho_te				-0.465	0.022		-0.466	0.021		-0.470	0.021		-0.253	0.019	
Rho_tn				0.224	0.056		0.178	0.021		0.000	-		0.239	0.055	
Rho_en				-0.071	0.048		-0.028	0.043		0.223	0.027		-0.041	0.046	
LogL	-4157.469			-73030.67			-73033.29			-73070.012			-73115.68		
n	31372			31372			31372			31372			31372		

Table 9 Estimated ATTs for Model 2

Panel A: Estimates of the ATT for unemployment, males

	Test scores						
Truancy	Ye1	Ye2	Ye3	Ye4	Ye5	Ye6	Total
Yt1	0	0	-0.071	-0.096	-0.112	-0.110	-0.099
	357	383	2306	4998	9666	2617	20327
Yt2	0	0	-0.093	-0.131	-0.167	-0.181	-0.131
	300	339	1395	2749	3118	470	8371
Yt3	0	0	-0.111	-0.157	-0.217	-0.230	-0.135
	143	137	403	619	368	41	1711
Yt4	0	0	-0.125	-0.184	-0.251	-0.273	-0.119
	109	64	105	130	78	7	493
Yt5	0	0	-0.136	-0.201	-0.281	-0.300	-0.079
	213	61	75	88	31	2	470
Total	0	0	-0.084	-0.114	-0.129	-0.123	-0.110
	1122	984	4284	8584	13261	3137	31372

Panel B: Estimates of the ATT for NEET, males

	Test scores						
Truancy	Ye1	Ye2	Ye3	Ye4	Ye5	Ye6	Total
Yt1	0	0	-0.085	-0.116	-0.143	-0.141	-0.124
	357	383	2306	4998	9666	2617	20327
Yt2	0	0	-0.106	-0.149	-0.196	-0.207	-0.151
	300	339	1395	2749	3118	470	8371
Yt3	0	0	-0.121	-0.171	-0.237	-0.242	-0.147
	143	137	403	619	368	41	1711
Yt4	0	0	-0.130	-0.189	-0.260	-0.291	-0.123
	109	64	105	130	78	7	493
Yt5	0	0	-0.141	-0.202	-0.278	-0.318	-0.080
	213	61	75	88	31	2	470
Total	0	0	-0.097	-0.133	-0.159	-0.152	-0.132
	1122	984	4284	8584	13261	3137	31372

Table 10 Estimated ATTS for model 2

Panel A Estimates of the ATT for unemployment, females

	Test scores						
Truancy	Ye1	Ye2	Ye3	Ye4	Ye5	Ye6	Total
Yt1	0	0	-0.061	-0.080	-0.086	-0.077	-0.079
	279	325	1567	5088	11176	4439	22874
Yt2	0	0	-0.082	-0.113	-0.136	-0.139	-0.117
	244	247	1176	3716	4659	1101	11143
Yt3	0	0	-0.099	-0.143	-0.178	-0.173	-0.129
	147	157	431	1019	682	80	2516
Yt4	0	0	-0.107	-0.164	-0.208	-0.207	-0.121
	134	75	142	287	157	13	808
Yt5	0	0	-0.123	-0.182	-0.245	-0.274	-0.089
	224	70	95	145	58	3	595
Total	0	0	-0.077	-0.102	-0.105	-0.091	-0.094
	1028	874	3411	10255	16732	5636	37936

Panel B Estimates of the ATT for NEET, females

	Test scores						
Truancy	Ye1	Ye2	Ye3	Ye4	Ye5	Ye6	Total
Yt1	0	0	-0.096	-0.119	-0.129	-0.113	-0.118
	279	325	1567	5088	11176	4439	22874
Yt2	0	0	-0.119	-0.154	-0.183	-0.179	-0.158
	244	247	1176	3716	4659	1101	11143
Yt3	0	0	-0.137	-0.184	-0.226	-0.224	-0.166
	147	157	431	1019	682	80	2516
Yt4	0	0	-0.148	-0.196	-0.247	-0.236	-0.147
	134	75	142	287	157	13	808
Yt5	0	0	-0.158	-0.216	-0.277	-0.275	-0.106
	224	70	95	145	58	3	595
Total	0	0	-0.113	-0.142	-0.149	-0.128	-0.133
	1028	874	3411	10255	16732	5636	37936

Table A1 Summary statistics, Males & Females

	Males				Females			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Cohort								
7	0.144	0.352	0	1	0.143	0.350	0	1
8	0.127	0.333	0	1	0.124	0.329	0	1
9	0.138	0.345	0	1	0.134	0.340	0	1
10	0.131	0.338	0	1	0.130	0.336	0	1
11	0.152	0.359	0	1	0.159	0.365	0	1
12	0.130	0.336	0	1	0.141	0.348	0	1
Ethnic background								
Afro-Caribbean	0.015	0.123	0	1	0.021	0.145	0	1
Indian	0.009	0.093	0	1	0.008	0.087	0	1
Bangladeshi/Pakistani	0.021	0.143	0	1	0.020	0.139	0	1
Other race	0.031	0.174	0	1	0.031	0.174	0	1
Unknown	0.025	0.156	0	1	0.026	0.159	0	1
Fathers occupation								
Professional/Managerial	0.167	0.373	0	1	0.166	0.372	0	1
Skilled non-manual	0.095	0.293	0	1	0.099	0.299	0	1
Skilled manual	0.131	0.337	0	1	0.123	0.328	0	1
Unskilled non-manual	0.182	0.385	0	1	0.188	0.390	0	1
Unknown	0.304	0.460	0	1	0.314	0.464	0	1
Mothers occupation								
Professional/Managerial	0.106	0.308	0	1	0.114	0.317	0	1
Skilled non-manual	0.109	0.312	0	1	0.111	0.314	0	1
Skilled manual	0.296	0.456	0	1	0.312	0.463	0	1
Unskilled non-manual	0.083	0.276	0	1	0.090	0.286	0	1
Unknown	0.333	0.471	0	1	0.305	0.460	0	1
Household status								
Father only	0.041	0.197	0	1	0.038	0.192	0	1
Mother only	0.126	0.332	0	1	0.151	0.358	0	1
School characteristics								
school size (pupil nos)	0.876	0.446	0.002	2.382	0.867	0.454	0.002	2.382
Pupil-teacher ratio	16.373	1.465	8.429	27.86	16.424	1.449	9.058	27.86
Eligibility for FSM	0.151	0.123	0	0.905	0.154	0.124	0	0.902
Voluntary-aided/control	0.155	0.362	0	1	0.155	0.362	0	1
Grant maintained	0.150	0.357	0	1	0.140	0.347	0	1
Secondary modern	0.038	0.191	0	1	0.039	0.194	0	1
Selective (i.e. Grammar)	0.033	0.179	0	1	0.036	0.186	0	1
Single sex	0.089	0.285	0	1	0.121	0.327	0	1
truan	0.010	0.012	0	0.135	0.010	0.011	0	0.163
truand	0.010	0.006	0.001	0.030	0.011	0.006	0.001	0.030
Region								
North/North East	0.085	0.279	0	1	0.085	0.279	0	1

Yorkshire & Humberside	0.116	0.320	0	1	0.112	0.315	0	1
North West	0.138	0.345	0	1	0.131	0.337	0	1
East Midlands	0.087	0.281	0	1	0.081	0.272	0	1
West Midlands	0.119	0.324	0	1	0.118	0.323	0	1
East Anglia/Eastern	0.088	0.283	0	1	0.090	0.286	0	1
South East (exc G. London)	0.174	0.379	0	1	0.179	0.383	0	1
South West	0.089	0.284	0	1	0.090	0.287	0	1
Sample size (n)	31,372				37,936			